Model-agnostic Approaches to Handling Noisy Labels When Training Sound Event Classifiers

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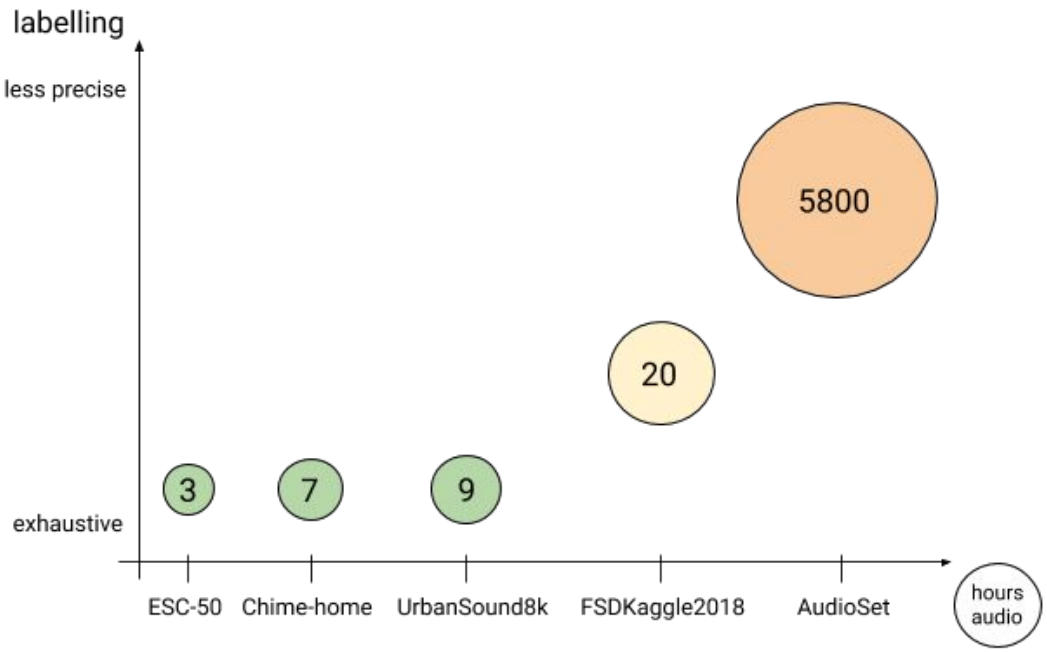
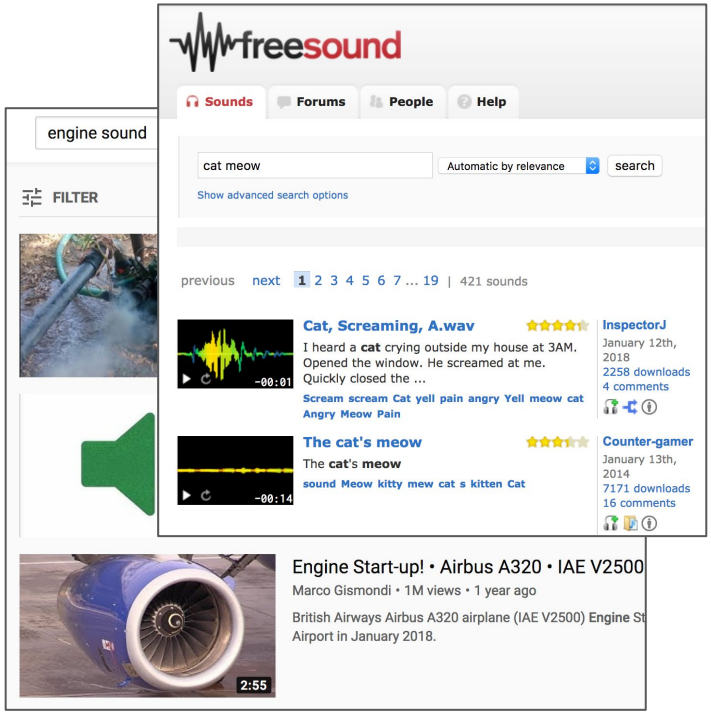
Label noise in sound event classification

- Labels that fail to properly represent acoustic content in audio clip
- Why is label noise relevant?





- Label noise effects: performance decrease / increased complexity

Our use case

- **Given a learning pipeline:**
  - → sound event dataset with noisy labels & deep network
  - → that we do not want to change
    - no network modifications / no additional (clean) data

- **How can we improve performance in THIS setting?**
  - → just minimal changes

Our use case

- **Given a learning pipeline**
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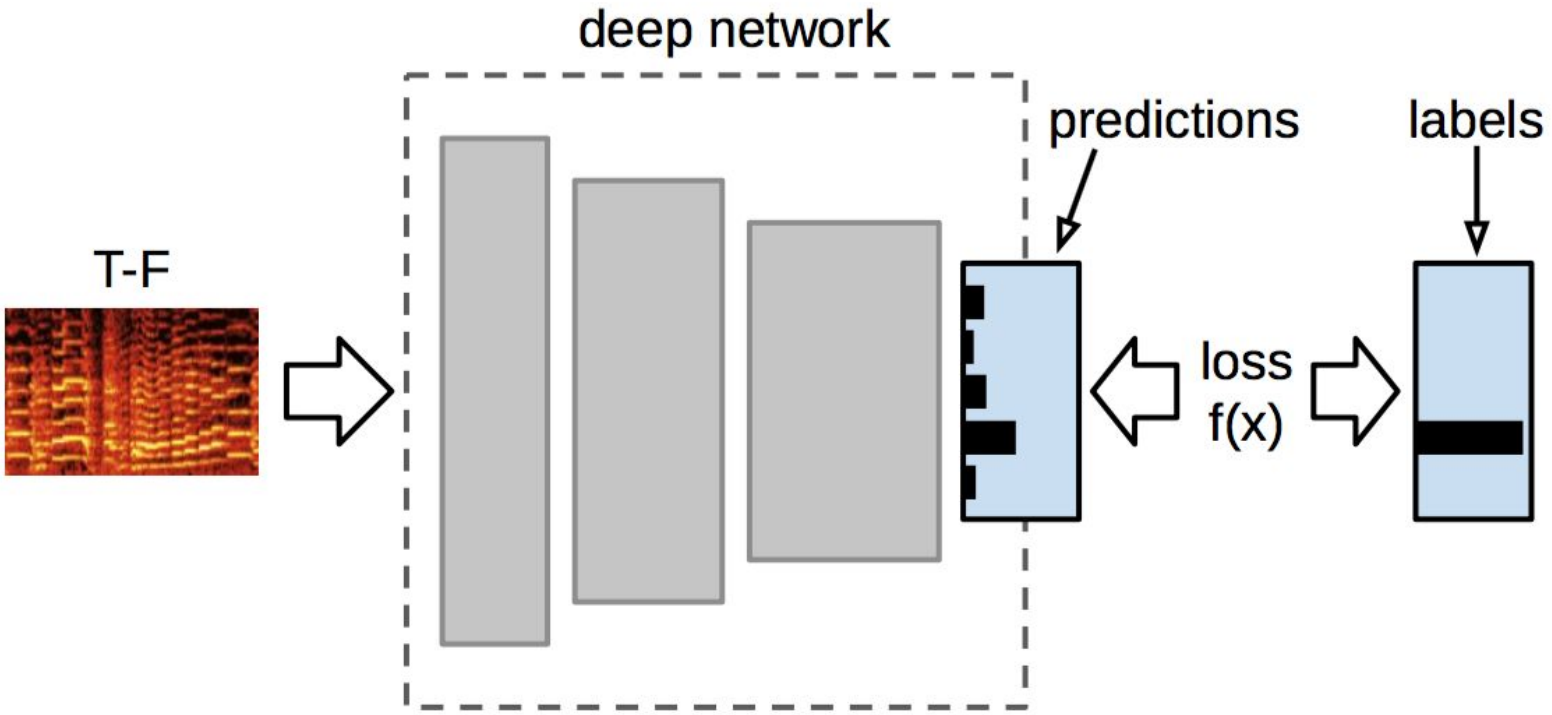
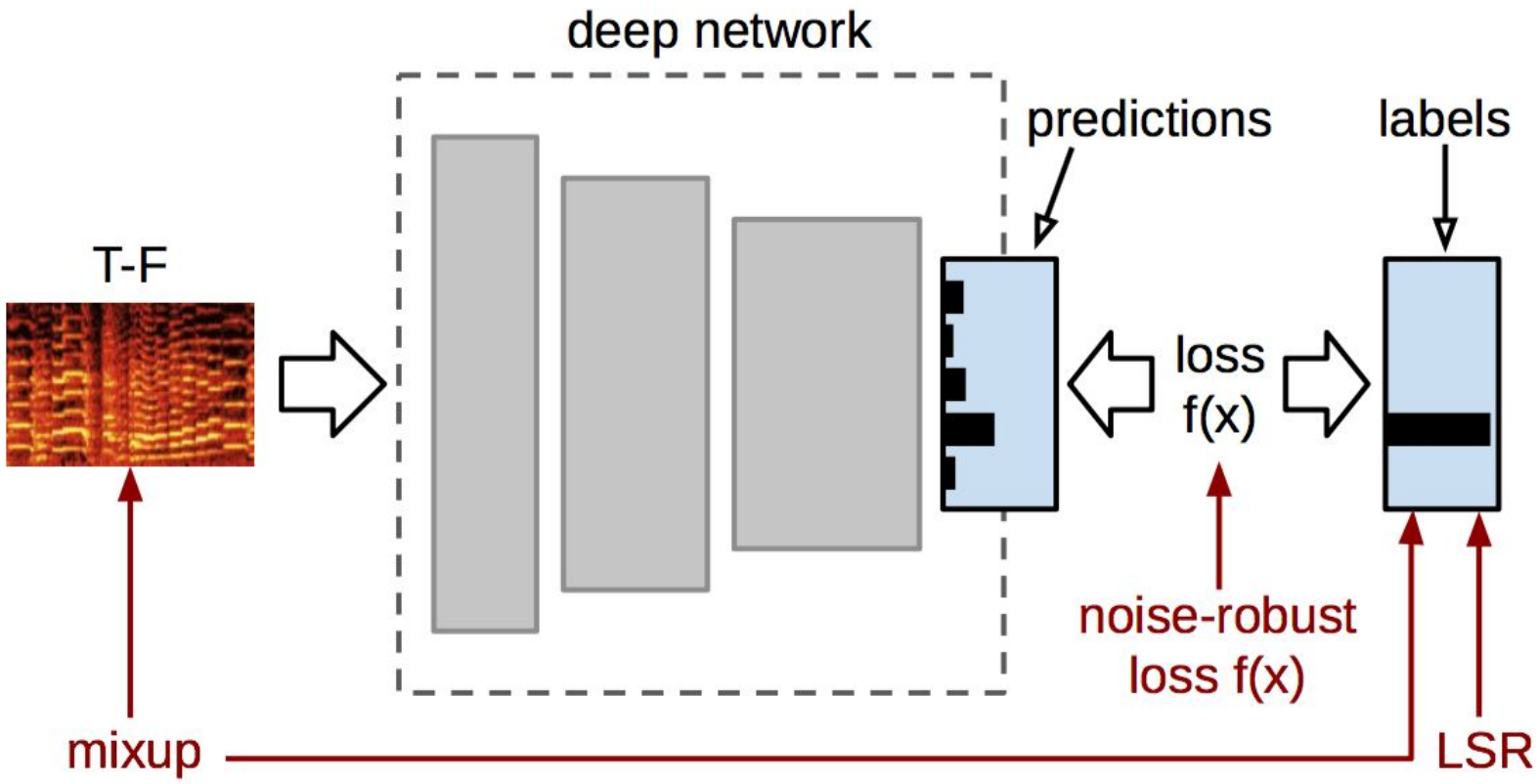
- **How can we improve performance in THIS setting?**
  - just minimal changes

- **Our work**
  - simple & efficient ways to boost performance in presence of noisy labels
  - agnostic to network architecture
  - that can be plugged into existing learning settings

Our use case

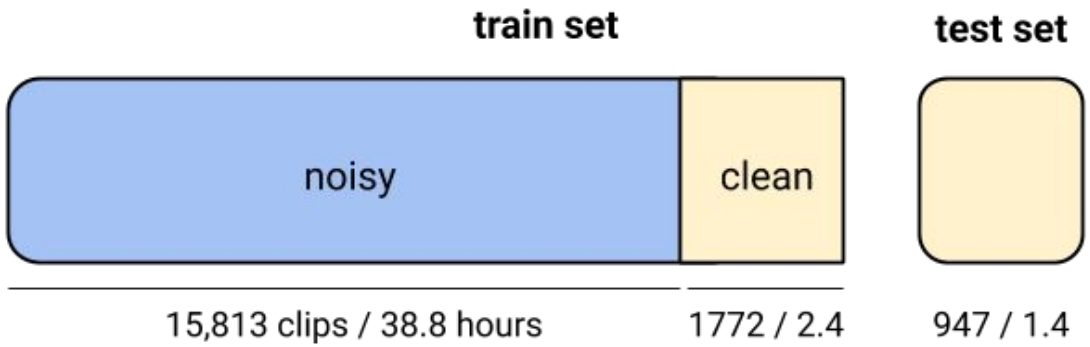


Our use case

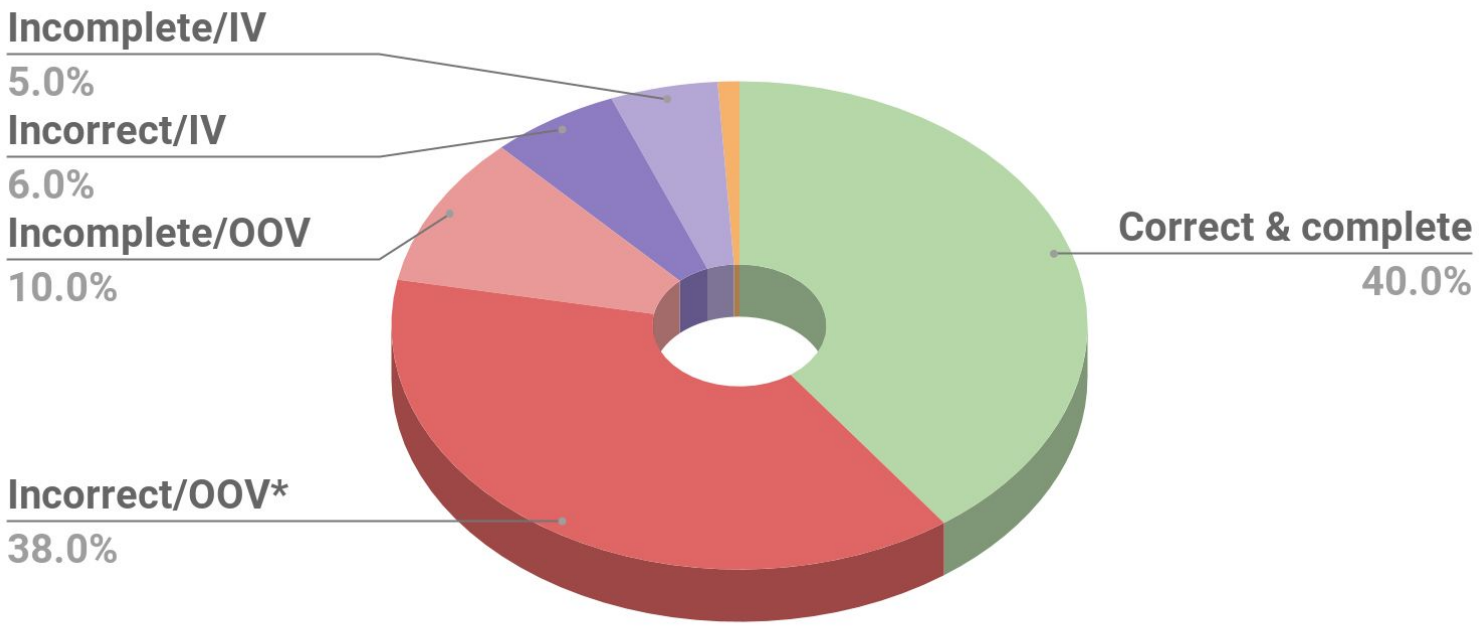

deep network
predictions
labels
T-F
loss
f(x)
noise-robust
loss f(x)
mixup
LSR

Dataset: FSDnoisy18k

- Freesound audio organized with 20 class labels from AudioSet Ontology
- audio content retrieved by user-provided tags
  - → per-class varying degree of types and amount of label noise
- 18k clips / 42.5 h
- singly-labeled data -> multi-class problem
- variable clip duration: 300ms - 30s
- proportion **train_noisy** / train_clean = 90% / 10%
- freely available http://www.eduardofonseca.net/FSDnoisy18k/

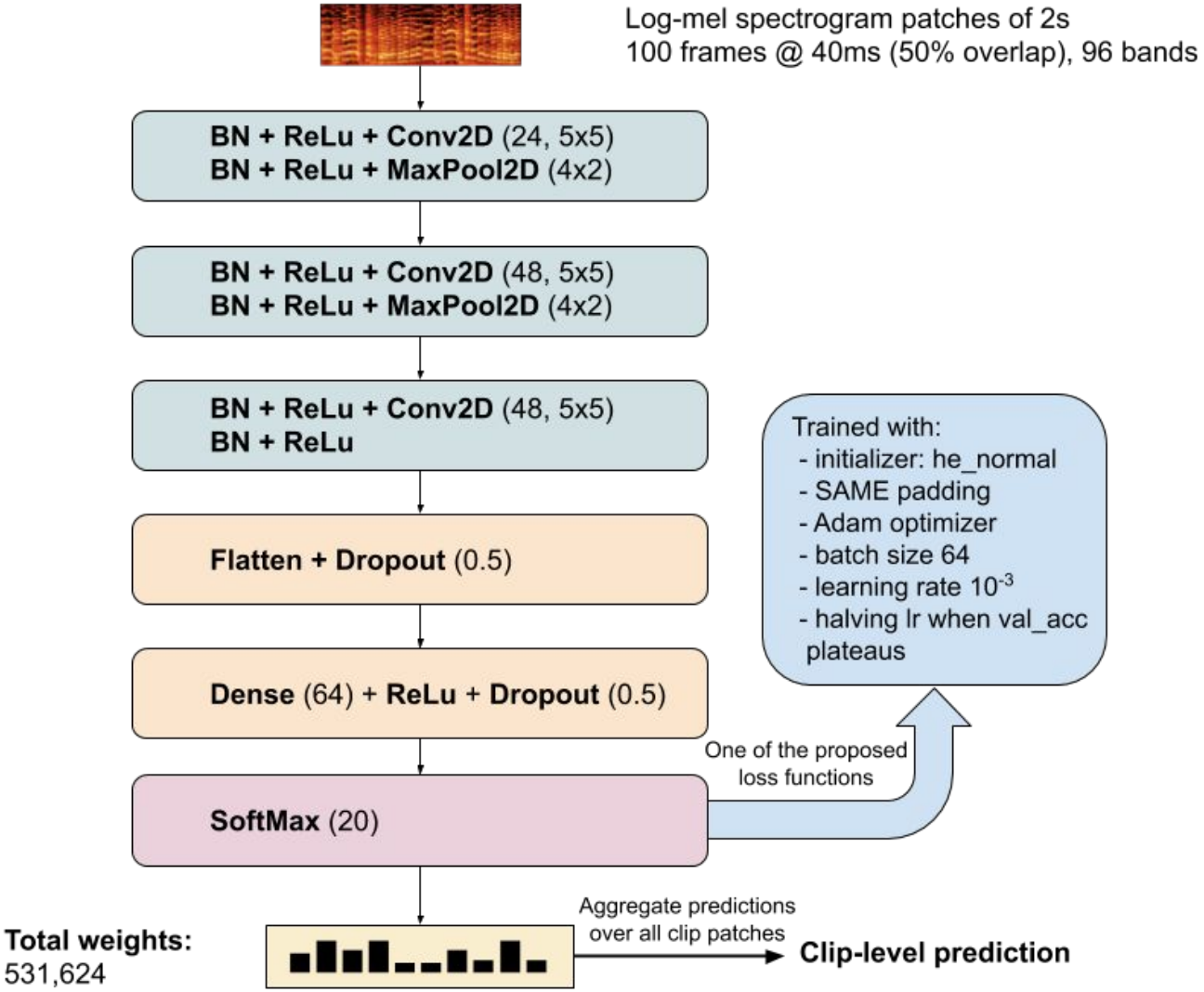


Label noise distribution in FSDnoisy18k



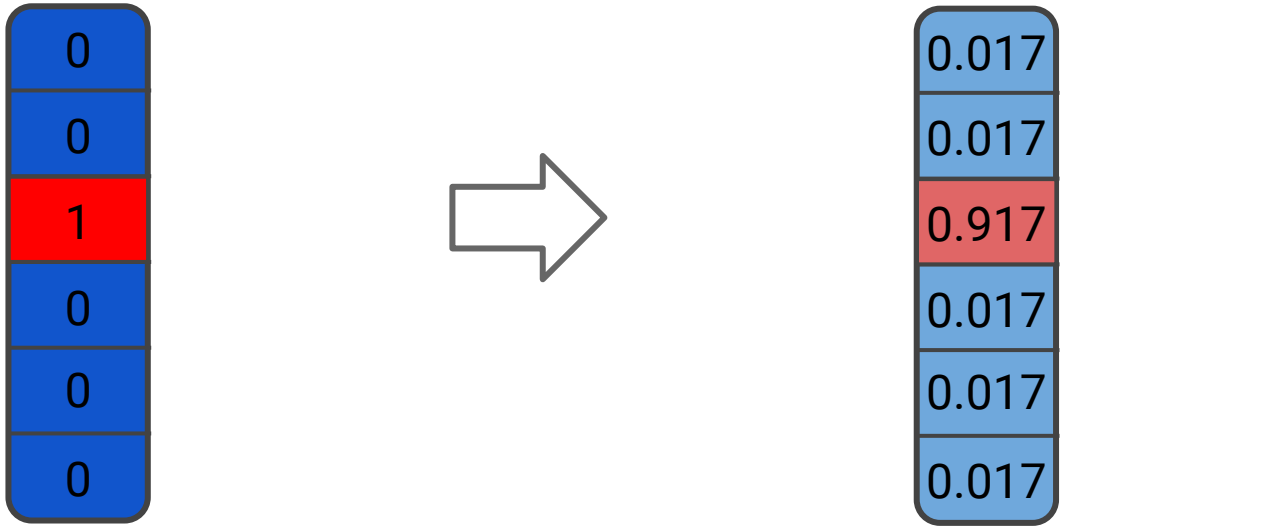
- IV: in-vocabulary, events that are part of our target class set
- OOV: out-of-vocabulary, events not covered by the class set

CNN baseline system



Label Smoothing Regularization (LSR)

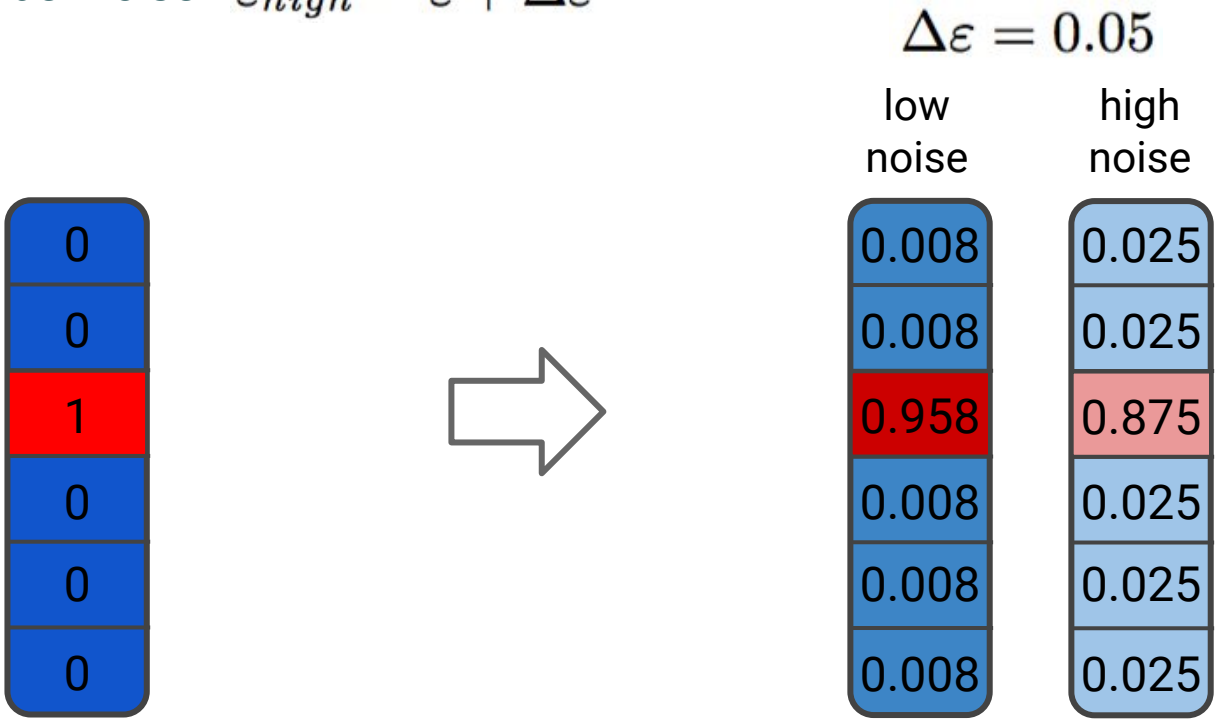
- Regularize the model by promoting less confident output distributions
  - → smooth label distribution: hard → soft targets



Noise dependent LSR

- Encode prior of label noise: 2 groups of classes:
  - low label noise $\varepsilon_{low} = \varepsilon - \Delta\varepsilon$
  - high label noise $\varepsilon_{high} = \varepsilon + \Delta\varepsilon$

$\Delta\varepsilon = 0.05$



LSR results

- Vanilla LSR provides limited performance
- Better by encoding prior knowledge of label noise through noise-dependent epsilon

Table 2: Average classification accuracy (%) and 95% confidence interval (7 runs) obtained by LSR incorporated to the baseline system.

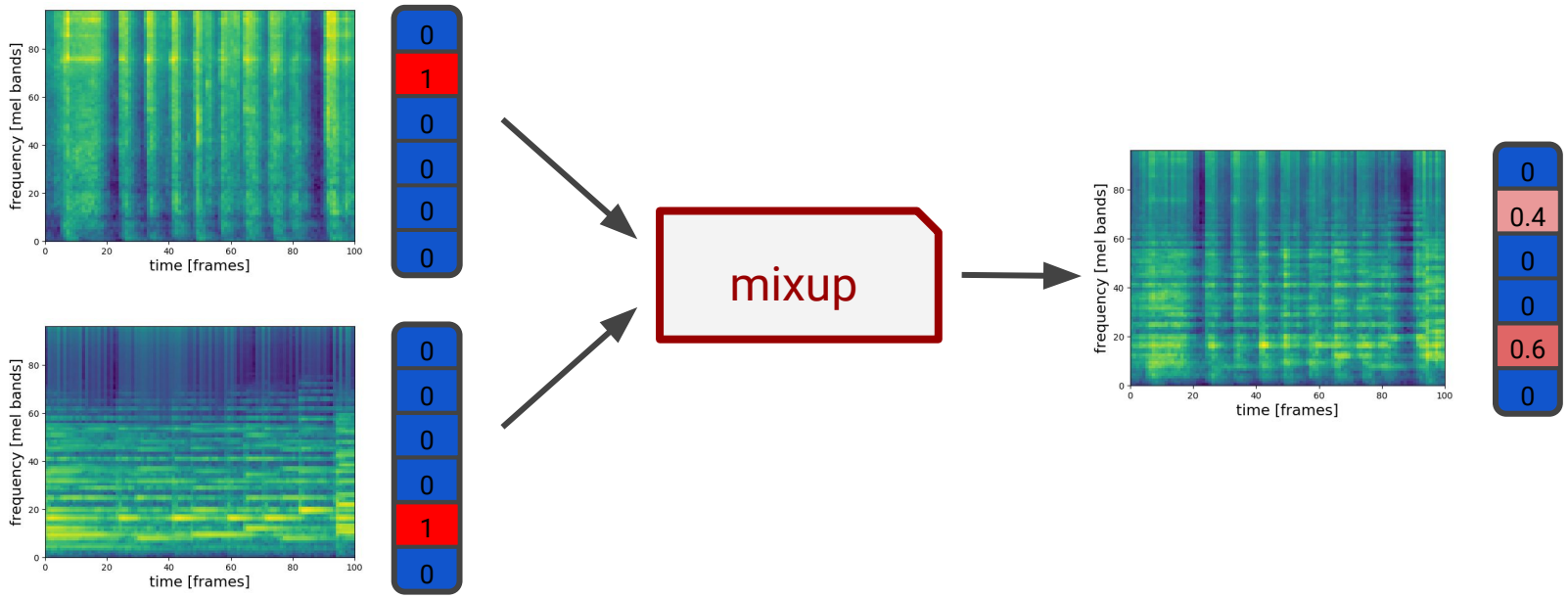
Approach	**Accuracy**
Baseline	66.5 ± 0.6
LSR ($\varepsilon = 0.1$)	66.8 ± 1.0
LSR ($\varepsilon = 0.15$)	67.1 ± 1.1
LSR ($\varepsilon = 0.15 \pm 0.05$)	68.1 ± 0.8

mix-up

- Linear interpolation
  - → in the feature space $\tilde{x} = \lambda x_i + (1 - \lambda) x_j$
  - → in the label space $\tilde{y} = \lambda y_i + (1 - \lambda) y_j$

$$\lambda \sim Beta(\alpha, \alpha)$$
$$\lambda \in [0, 1]$$

- Again, soft targets



mix-up results

- mix-up applied from the beginning: limited boost
- creating virtual examples far from the training distribution confuses the model
- warming-up the model helps!

Table 2: Average classification accuracy (%) and 95% confidence interval (7 runs) obtained by LSR and mixup incorporated to the baseline system.

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LSR ($\varepsilon = 0.1$)	66.8 ± 1.0
LSR ($\varepsilon = 0.15$)	67.1 ± 1.1
LSR ($\varepsilon = 0.15 \pm 0.05$)	68.1 ± 0.8
mixup ($\alpha = 0.1$)	67.1 ± 0.8
mixup ($\alpha = 0.2$)	66.6 ± 0.7
warm-up (10 epochs) & mixup ($\alpha = 0.3$)	$\mathbf{68.4} \pm 0.5$

Noise-robust loss function

Noise-robust loss function

- Default loss function in multi-class setting: Categorical Cross-Entropy (CCE)

$$\mathcal{L}_{cce} = -\sum_{k=1}^{K} y(k) \log(p(k))$$

predictions

target labels

Noise-robust loss function

- Default loss function in multi-class setting: Categorical Cross-Entropy (CCE)

$$\mathcal{L}_{cce} = -\sum_{k=1}^{K} y(k) \log(p(k))$$

- CCE is sensitive to label noise: emphasis on *difficult* examples (weighting)
  - → beneficial for clean data
  - → detrimental for noisy data

Noise-robust loss function

- $\mathcal{L}_q$ loss intuition
  - CCE: sensitive to noisy labels (weighting)
  - Mean Absolute Error (MAE): $\mathcal{L}_{mae} = \sum_{k=1}^{K} |y(k) - p(k)|$
    - avoid weighting
    - difficult convergence

Zhilu Zhang and Mert Sabuncu, ***Generalized cross entropy loss for training deep neural networks with noisy labels***. In NeurIPS 2018

Noise-robust loss function

- $\mathcal{L}$q loss intuition
  - CCE: sensitive to noisy labels (weighting)
  - Mean Absolute Error (MAE): $\mathcal{L}_{mae} = \sum_{k=1}^{K} |y(k) - p(k)|$
    - avoid weighting
    - difficult convergence
- $\mathcal{L}$q loss is a generalization of CCE and MAE:
  - negative Box-Cox transformation of softmax predictions

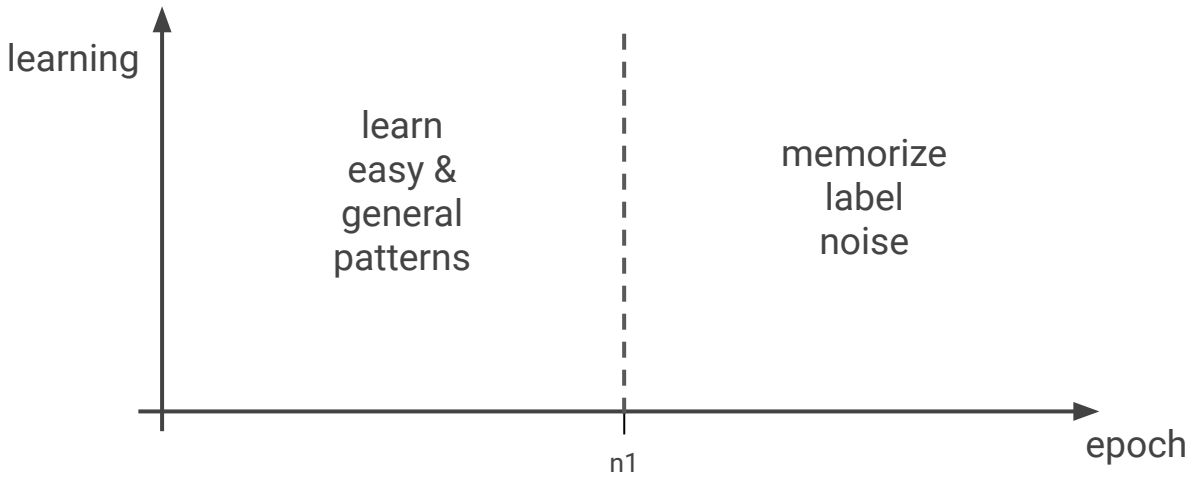
$$\mathcal{L}_q = \frac{1 - (\sum_{k=1}^{K} y(k)p(k))^q}{q}, \quad q \in (0, 1]$$

  - $q = 1 \rightarrow \mathcal{L}$q = MAE ; $q \rightarrow 0 \rightarrow \mathcal{L}$q = CCE

Zhilu Zhang and Mert Sabuncu, ***Generalized cross entropy loss for training deep neural networks with noisy labels***. In NeurIPS 2018

Learning and noise memorization

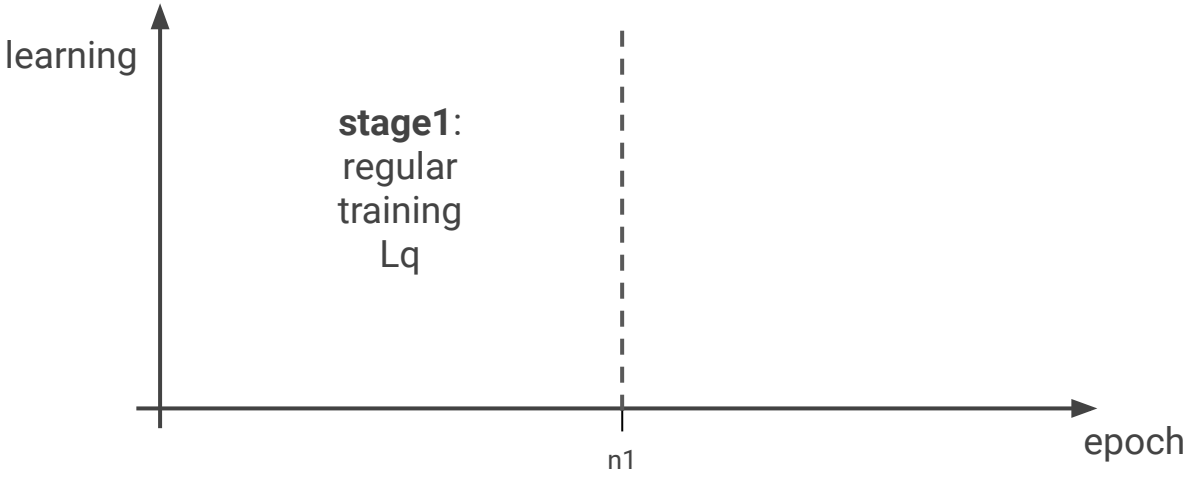
- Deep networks in presence of label noise
  - → problem is more severe as learning progresses



Arpit, Jastrzebski, Ballas, Krueger, Bengio, Kanwal, Maharaj, Fischer, Courville, and Bengio., ***A closer look at memorization in deep networks***. In ICML 2017

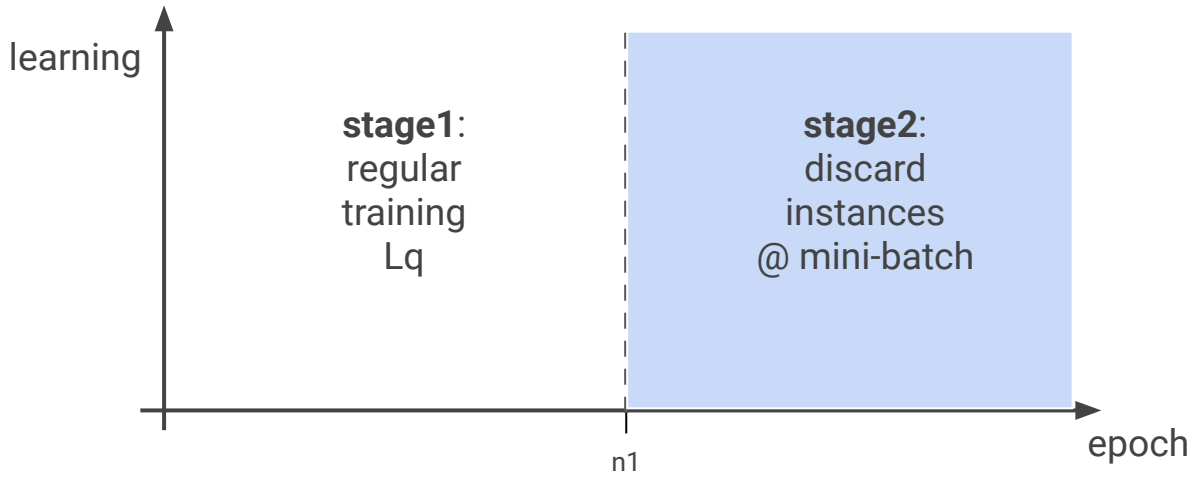
Learning as a two-stage process

- Learning process as a two-stage process
- After n1 epochs:
  - → model has converged to some extent
  - → use it for instance selection
    - identify instances with large training loss
    - ignore them for gradient update



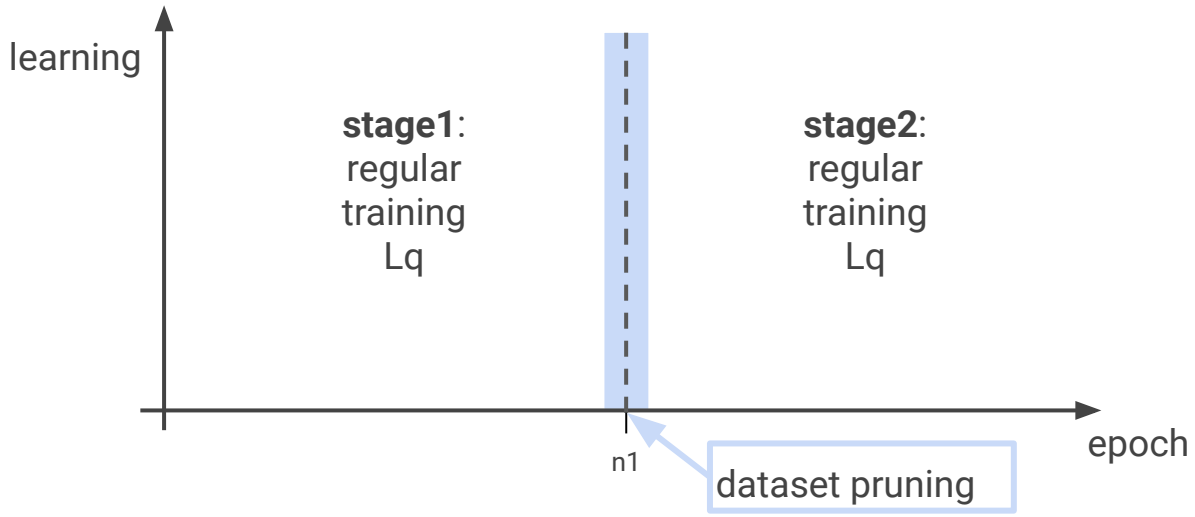
Ignoring large loss instances

- Approach 1:
  - **discard** large loss instances **from each mini-batch** of data
  - dynamically at every iteration
  - time-dependent loss function



Ignoring large loss instances

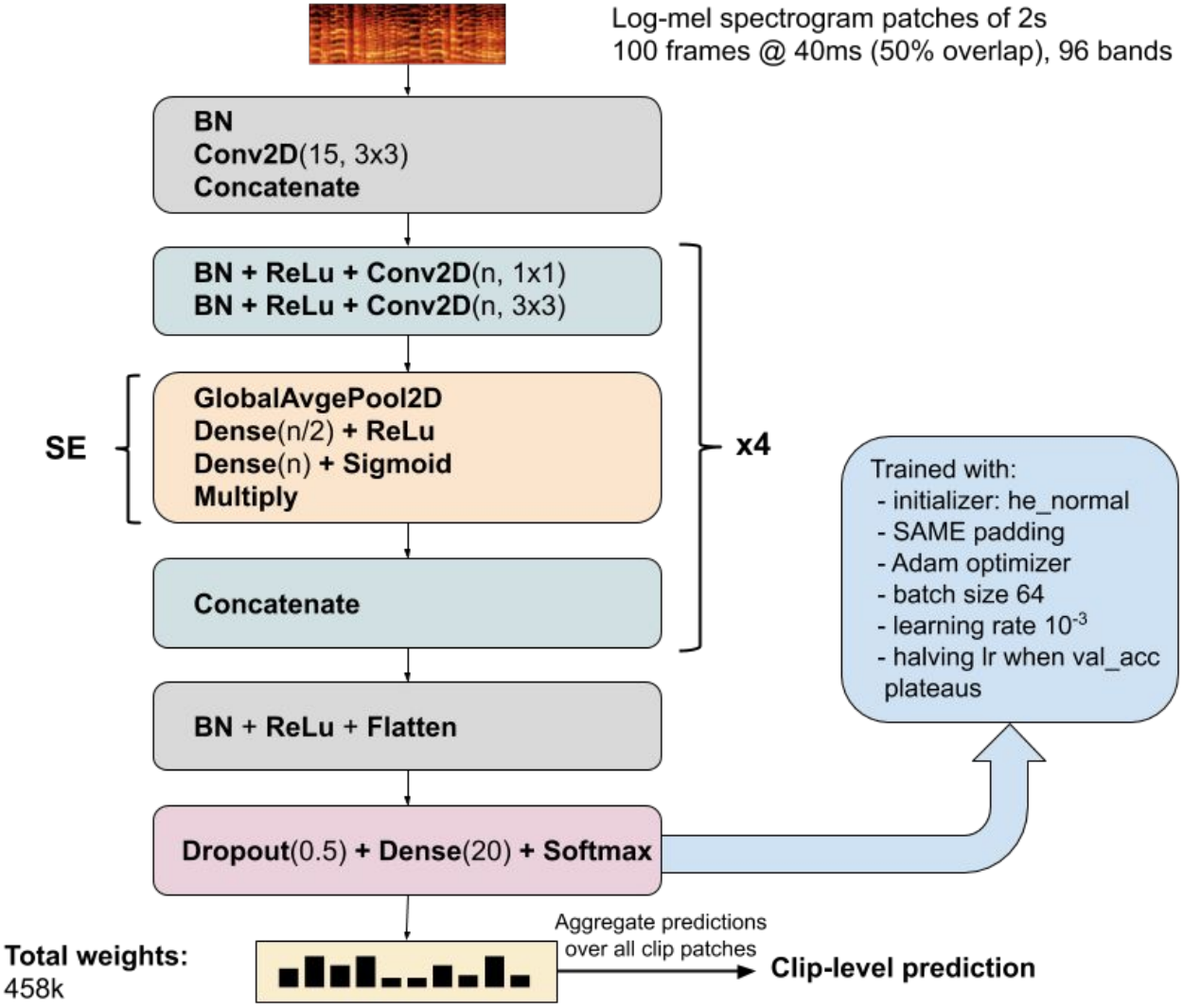
- Approach 2:
  - use checkpoint to predict scores on whole dataset
  - convert to loss values
  - **prune dataset**, keeping a subset to continue learning



Noise-robust loss function results

- We report results with two models
  - using baseline
  - using a more accurate model

A more accurate model: DenSE



Noise-robust loss function results

- pruning dataset slightly outperforms discarding at mini-batch

Table 4: Average classification accuracy (%) and 95% confidence interval (7 runs) obtained by loss function approaches.

Approach	**Baseline**	**DenSE**
CCE	66.5 ± 0.6	67.9 ± 0.7
$\mathcal{L}_q$	68.4 ± 0.5	69.2 ± 0.8
$\mathcal{L}_{q,discard}$ (discard at mini-batch)	68.8 ± 0.9	69.8 ± 0.7
$\mathcal{L}_{q,prune}$ (prune dataset)	$\mathbf{69.0} \pm 0.6$	$\mathbf{70.2} \pm 0.5$

Noise-robust loss function results

- pruning dataset slightly outperforms discarding at mini-batch
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Noise-robust loss function results

- pruning dataset slightly outperforms discarding at mini-batch
- discarding at mini-batch is less stable
- DenSE:
  - → higher boosts wrt $\mathcal{L}_q$
  - → more stable

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Summary & takeaways

- Three simple model agnostic approaches against label noise
  - → easy to incorporate to existing pipelines
  - → minimal computational overhead
  - → absolute accuracy boosts ~ 1.5 - 2.5%

- Most promising: pruning dataset using model as instance selector
  - → could be done several times iteratively
  - → useful for dataset cleaning
  - → but dependent on pruning time & pruned amount

Model-agnostic Approaches to Handling Noisy Labels When Training Sound Event Classifiers

Thank you!

https://github.com/edufonseca/waspaa19

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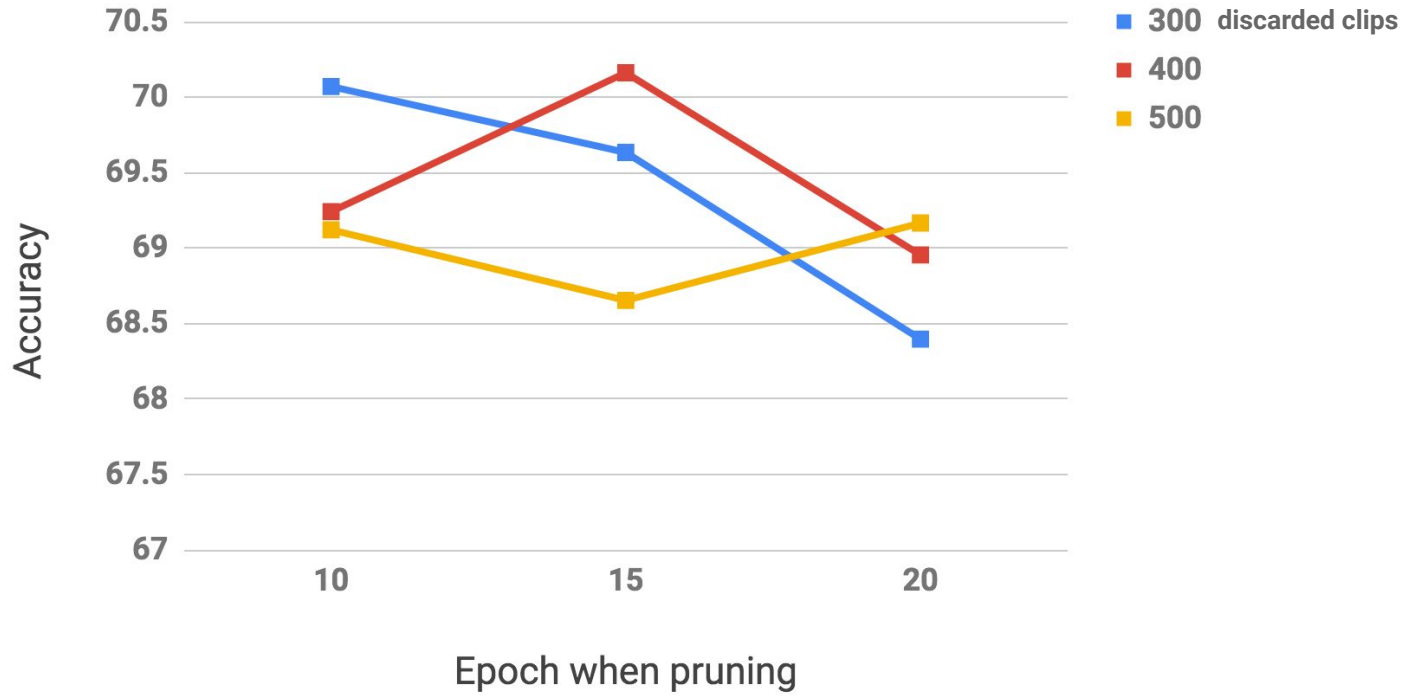
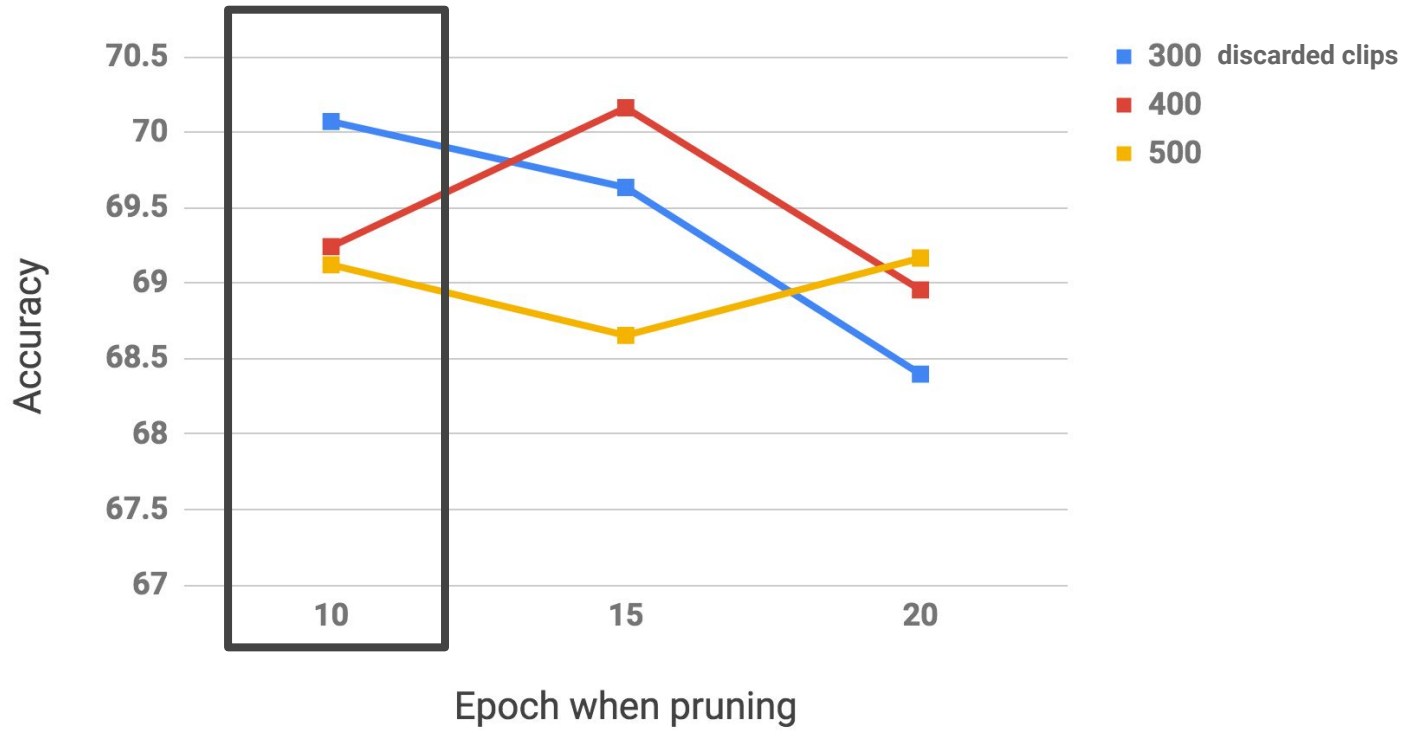
Dataset pruning & noise memorization

- We explore pruning the dataset at different epochs



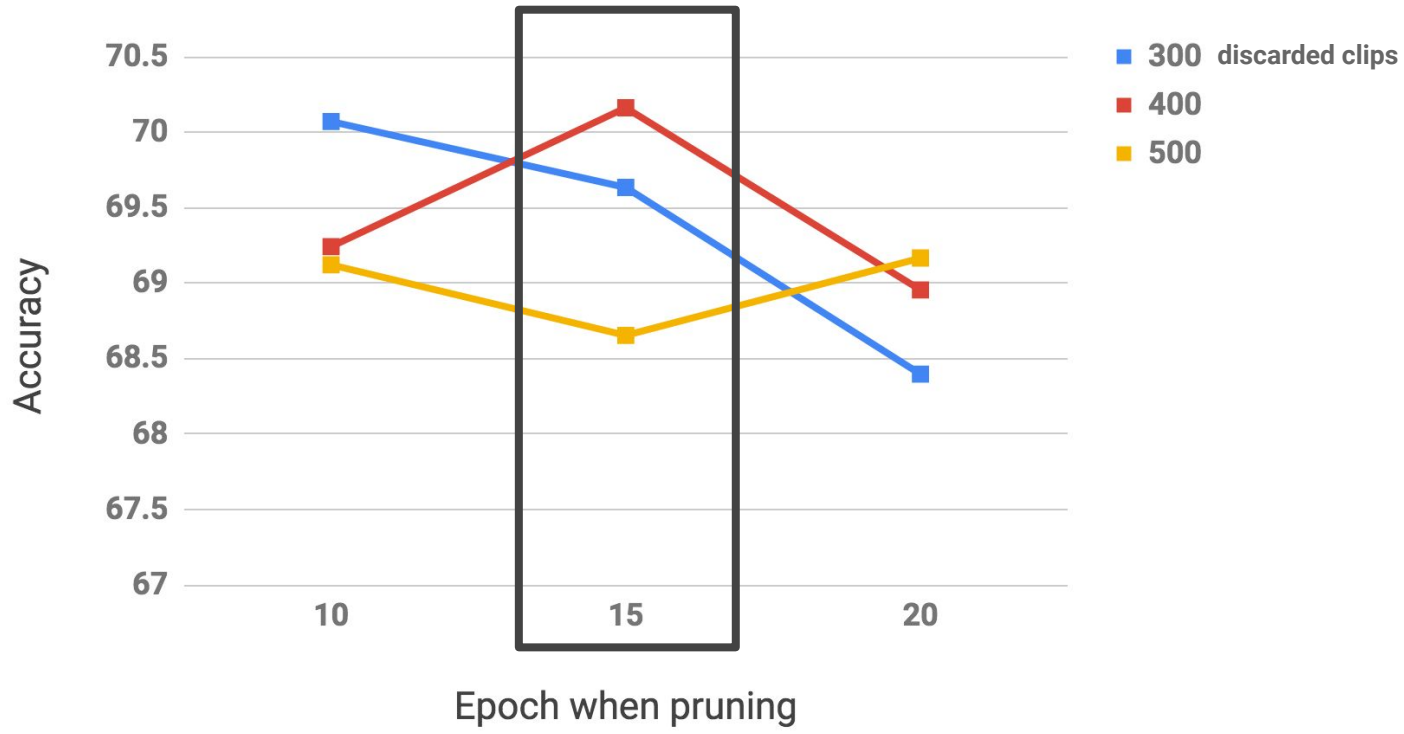
Dataset pruning & noise memorization

- model not too accurate ➔ pruning many clips is worse



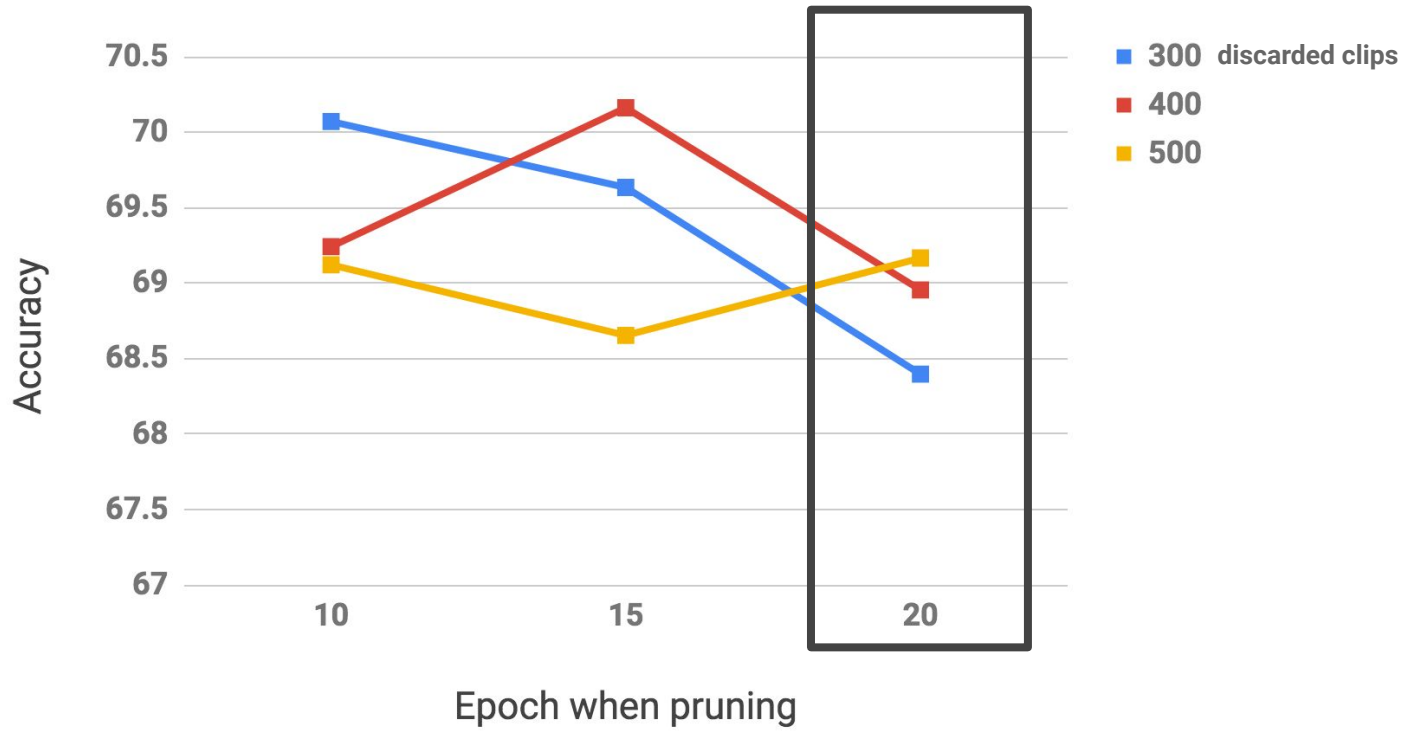
Dataset pruning & noise memorization

- model is more accurate ➜ allows larger pruning (to a certain extent)



Dataset pruning & noise memorization

- model start to memorize noise?



Why this vocabulary?

- data availability
- classes “suitable” for the study of label noise
  - → classes described with tags also used for other audio materials
    - Bass guitar, Crash cymbal, Engine, …
  - → field-recordings: several sound sources expected
    - only the most predominant(s) tagged: Rain, Fireworks, Slam, Fire, …
  - → pairs of related classes:
    - Squeak & Slam / Wind & Rain

Acoustic guitar / Bass guitar / Clapping / Coin (dropping) / Crash cymbal / Dishes, pots, and pans / Engine / Fart / Fire / Fireworks / Glass / Hi-hat / Piano / Rain / Slam / Squeak / Tearing / Walk, footsteps / Wind / Writing